Unsupervised learning for real-time SUEP detection in a high-level trigger system at the LHC

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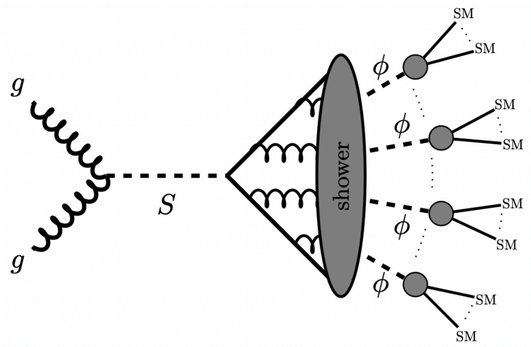
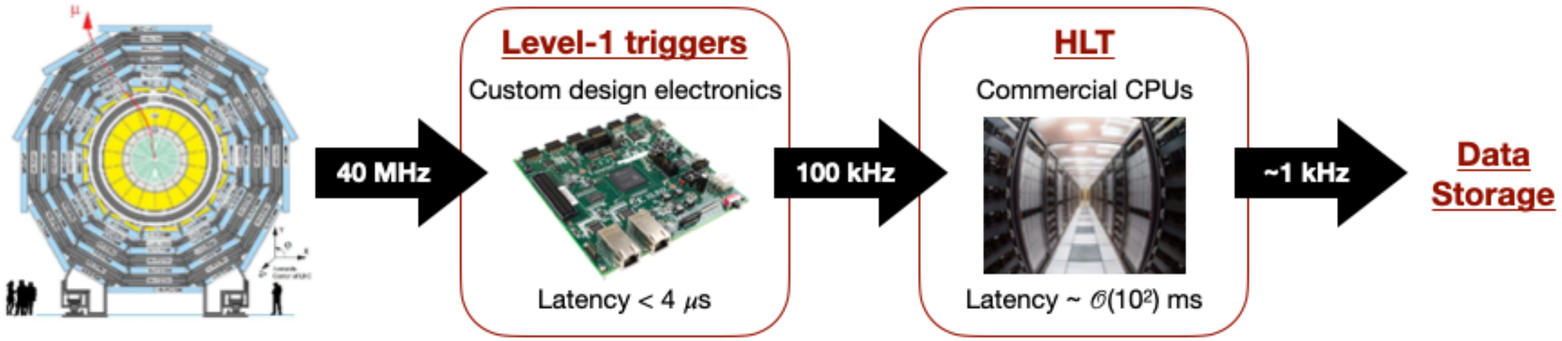
Motivation

- A new paradigm for data-driven, model-agnostic **new physics searches at colliders** is emerging
  - Aims to leverage recent breakthroughs in **anomaly detection (AD) techniques** exploiting **artificial intelligence (AI)** [Dark Machines, LHC Olympics 2020]
- Most of the AD techniques using *offline reconstructed data* assume that the particle reconstruction is effective, but **what if it's not the case?**



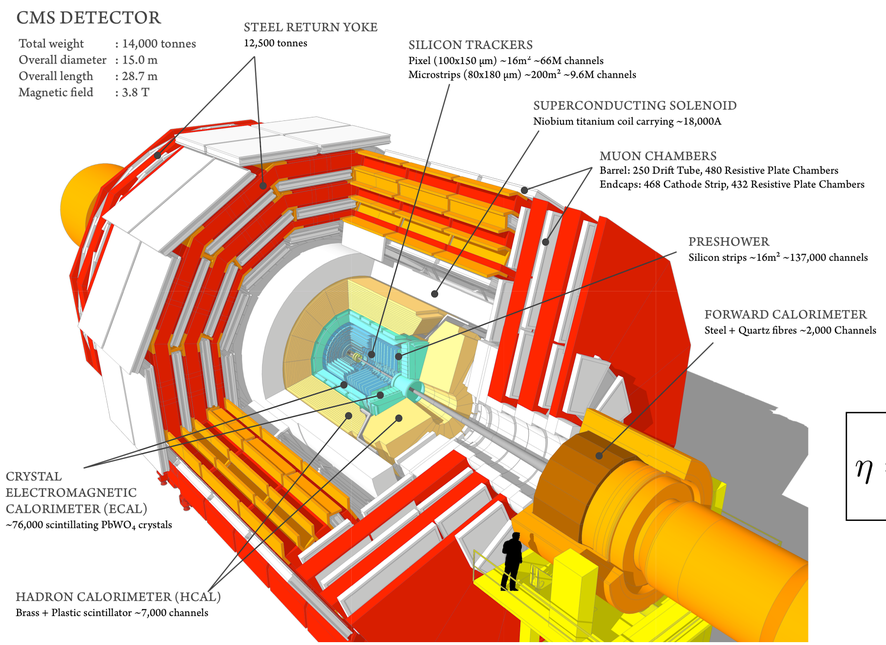
- **GOAL:** develop an AI algorithm for **real-time detection of anomalous, non-QCD-like, events, in a high-level trigger (HLT) system at the LHC**, where QCD is an overwhelming background for several new physics searches
  - Use case: for **Soft Unclustered Energy Patterns (SUEP)** detection [JHEP 08 (2017) 076], in the **CMS HLT system** [JINST 12 (2017) P01020]

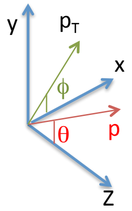


Methodology

- **A computer-vision problem:**
  - data are represented as RGB images
  - Energy deposits (in η-ϕ plane) in the inner-tracker, ECAL and HCAL sub-detectors of the CMS detector
- Exploit a **convolutional neural networks-based autoencoder** (or ConvAE) to learn what a typical QCD event looks like and **focus on outliers**

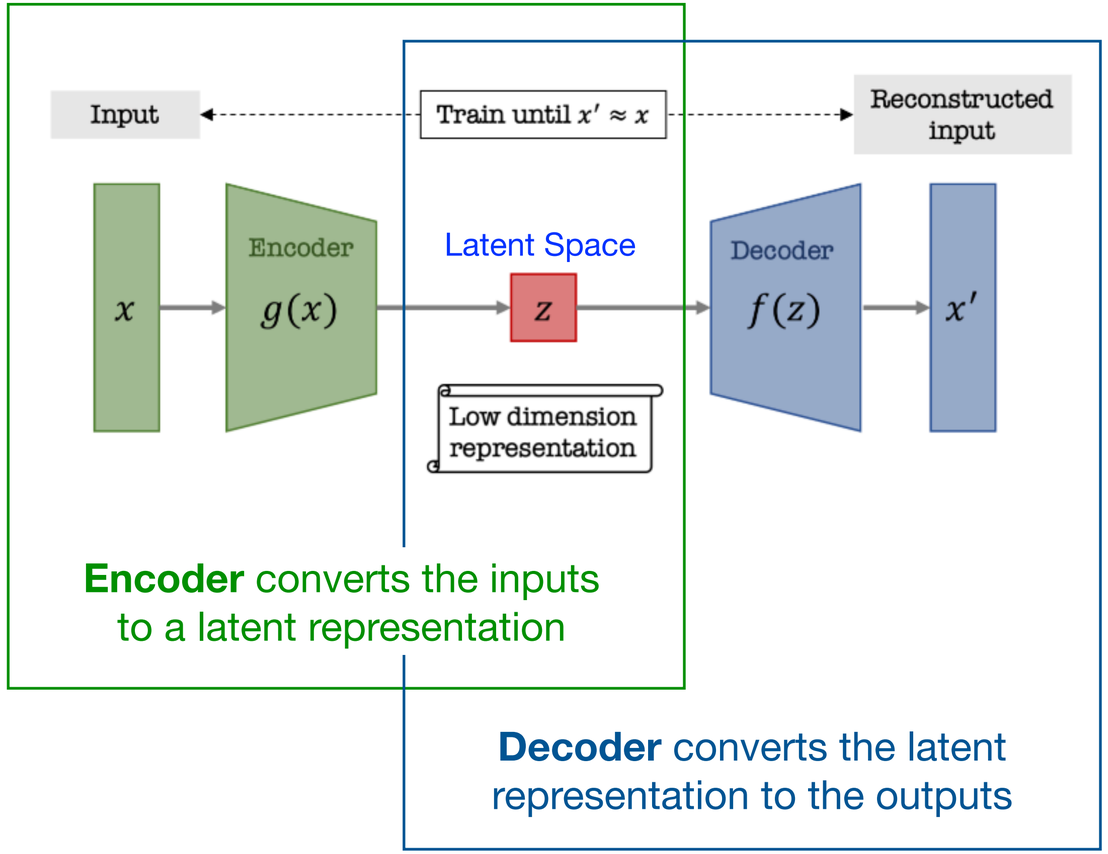
The CMS Experiment [JINST 3 (2008) S08004]





$$\eta = -ln \tan \frac{\theta}{2}$$

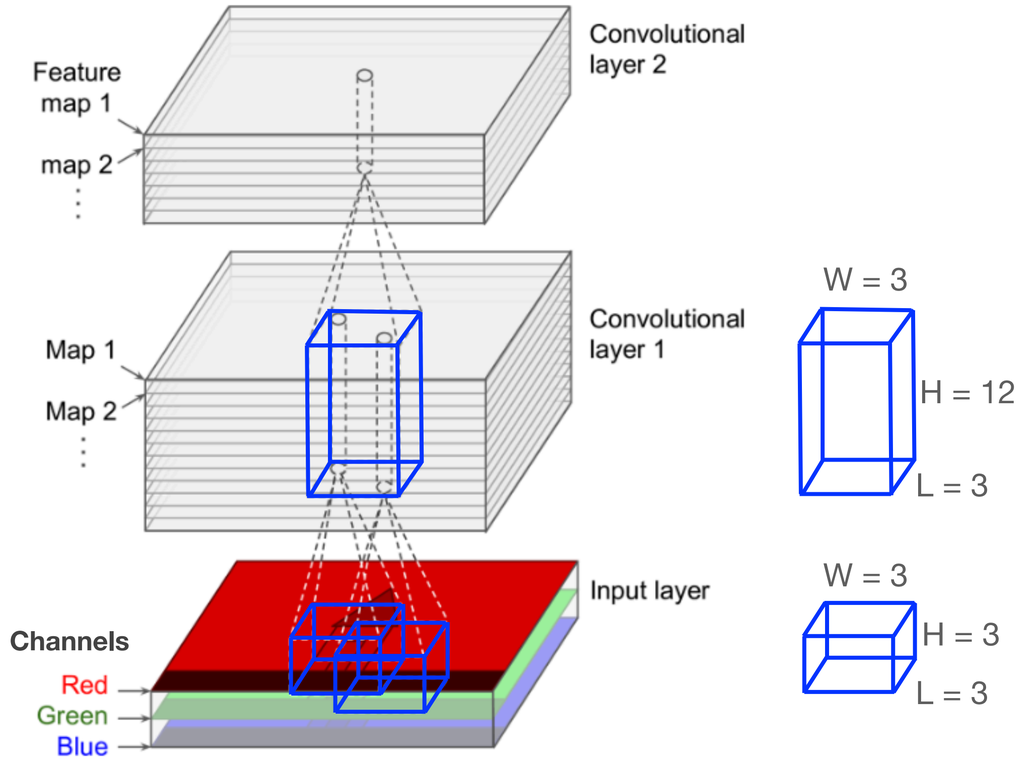
Autoencoders



Reconstruction loss penalises the model when the reconstructions are different from the inputs

For more details: this book

Convolutional Neural Networks



E.g., RGB image convolution to layer 1

Input to feature map 1 of convolutional layer 1

$z_i = b_0 + \sum x_i w_i$ where $i = 0$ to 26

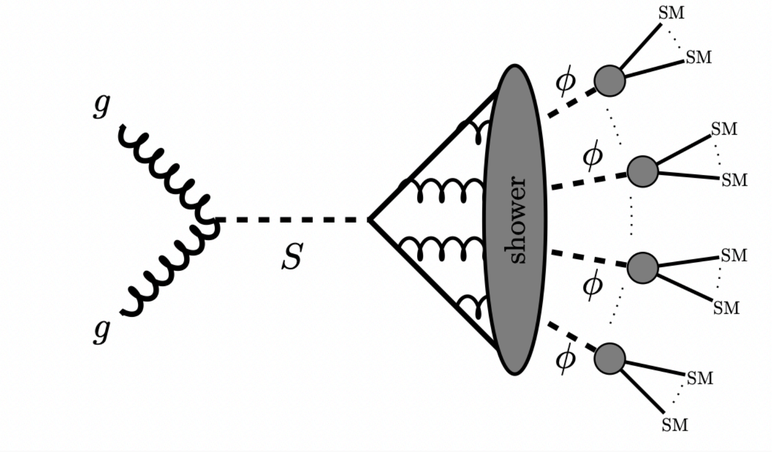
generalising for all feature maps

$z_{ik} = b_k + \sum x_i w_{ik}$ where $k = 0$ to 11

Trainable parameters
Biases (b_k): 12
Weights (w_{ik}): 27x12
Total = 336

Events generation/simulation and selection

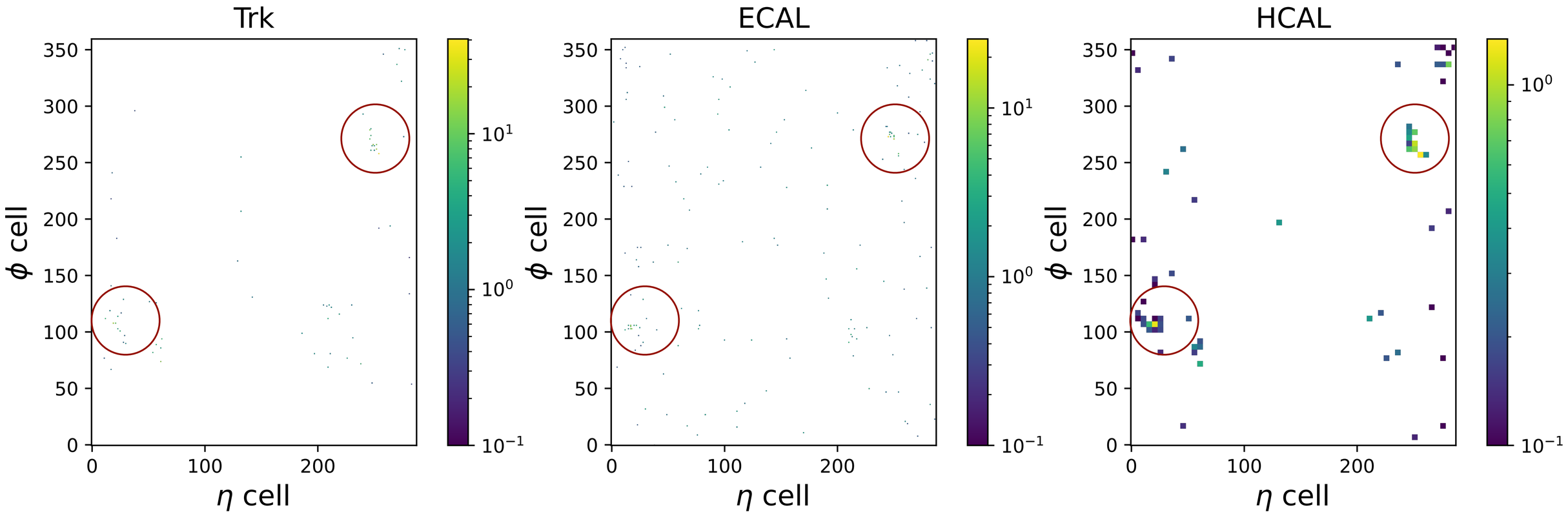
- **Generation:** Pythia8.244
  - Center-of-mass energy = 13.6 TeV
  - **QCD:** 1M events
  - **SUEP:** 100k events per scalar boson (S) mass value
    - S mass = {125, 400, 700, 1000} GeV
    - Dark meson mass = 2 GeV and BR = 100% (2 dark photons)
    - Dark photon mass = 0.7 GeV and BR = 15% (e^+e^-), 15% ($\mu^+\mu^-$), 70% ($\pi^+\pi^-$)
    - Dark temperature = 2 GeV



- **Simulation:** Delphes3.5.0 (<#pile-up events> = 50)

Energy deposits for a QCD event

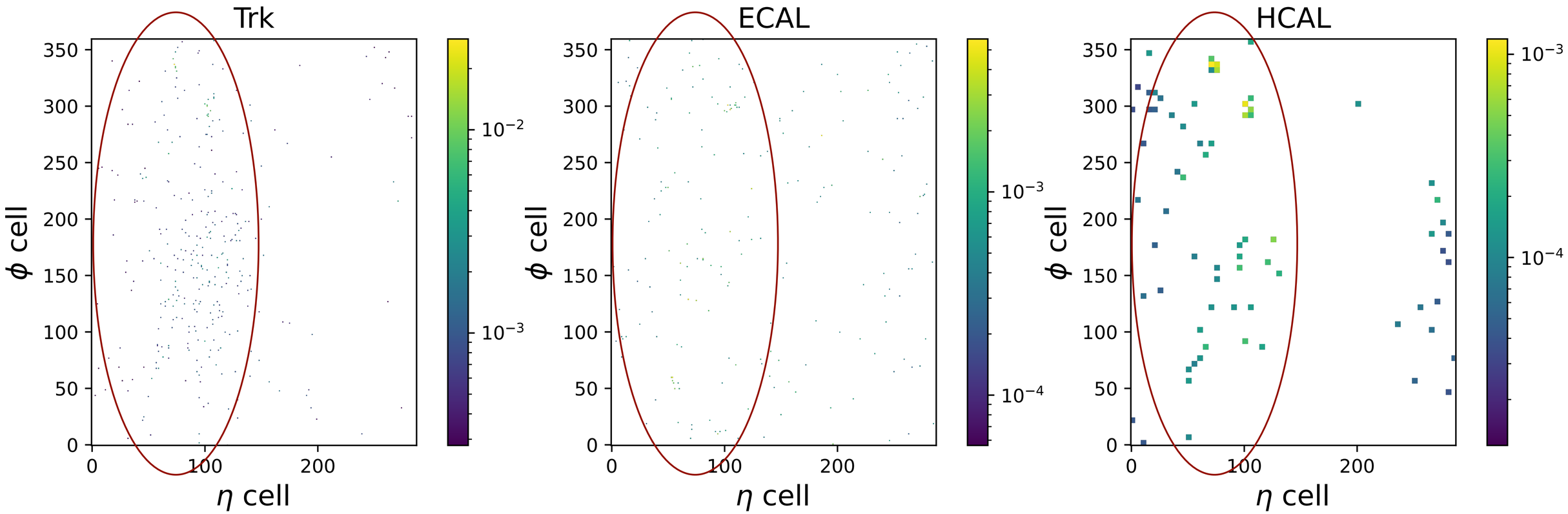
- Total pixels = 288x360x3 **~0.3 megapixels**, defined by ECAL granularity
- HCAL granularity = ECAL granularity / 25 → each HCAL pixel is divided in to 25 pixels and as well the pixel energy



- **Highly-sparse data:** ~0.5% (~1.6k) pixels have $E_T > 0$ GeV

Energy deposits for a SUEP(1 TeV) event

- A clear **anomalous (spherically-symmetric in ϕ) signature wrt QCD!**



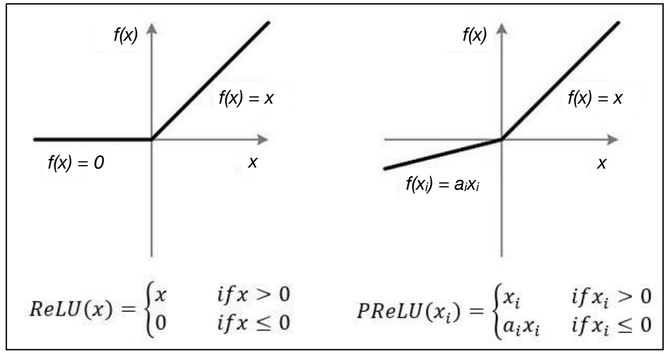
ConvAE architecture

	Layer(kernel size, strides)	Shape	BatchNorm	Activation
	Input	(288, 360, 3)		
ENCODER	Conv2D(3, 3)	(96, 120, 128)	yes	PReLU
ENCODER	Conv2D(3, 2)	(48, 60, 64)	yes	PReLU
ENCODER	Conv2D(3, 2)	(24, 30, 32)	yes	PReLU
ENCODER	Conv2D(3, 2)	(12, 15, 16)	yes	PReLU
LS	Conv(3, (2, 3))	(6, 5, 8)	yes	PReLU
DECODER	Conv2DTrans(3, (2, 3))	(12, 15, 16)	yes	PReLU
DECODER	Conv2DTrans(3, 2)	(24, 30, 32)	yes	PReLU
DECODER	Conv2DTrans(3, 2)	(48, 60, 64)	yes	PReLU
DECODER	Conv2DTrans(3, 2)	(96, 120, 128)	yes	PReLU
DECODER	Conv2DTrans(3, 3)	(288, 360, 3)	yes	ReLU

Optimiser = Adam(lr = 0.001)

Total trainable parameters = 3,574,065

ReLU **PReLU**



- **Data pre-processing:** data are normalised such that they are of $\mathcal{O}(1)$ → stable learning process

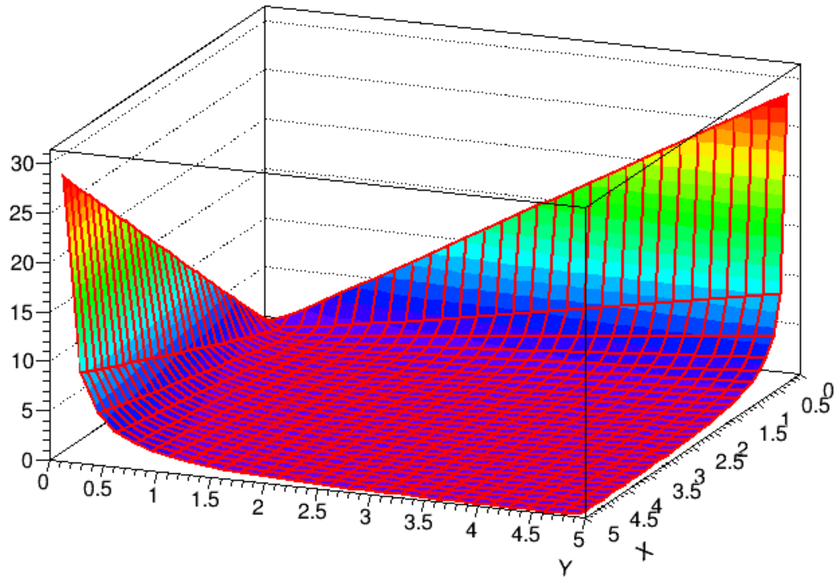
ConvAE training

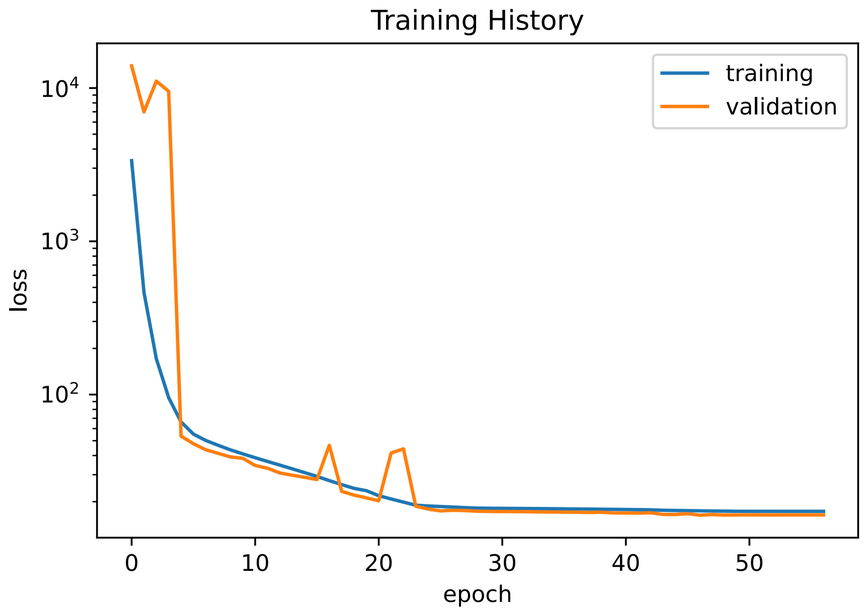
- Commonly-used loss functions such as MSE, MAE, Huber, and cross entropy failed due to highly sparse nature of data
- We use **1/Dice coefficient** [arXiv:1807.10097] as a loss function, which focuses on similarity of input and output pixels

$$\text{Loss} = \frac{\sum(X^2)+\sum(Y^2)}{2\times\sum(X\cdot Y)} - 1 \ (X = \text{input};\ Y = \text{output})$$

X_{train} : 50k QCD events
X_{val} : 50k QCD events
batch size = 128

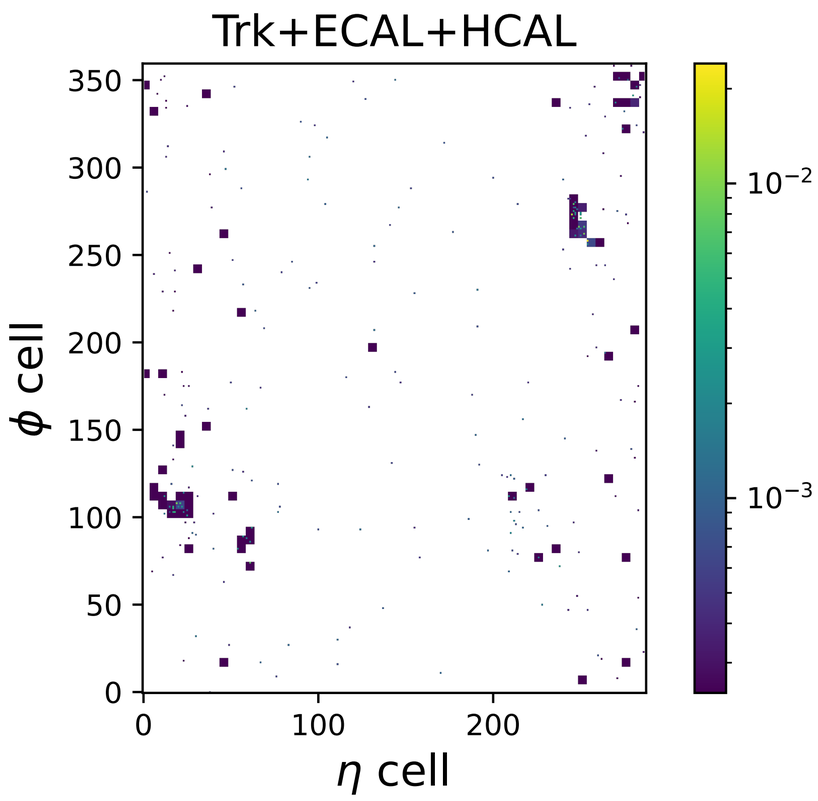
GPU: NVIDIA Tesla V100 PCIe 32 GB
Training time/epoch: ~25 min



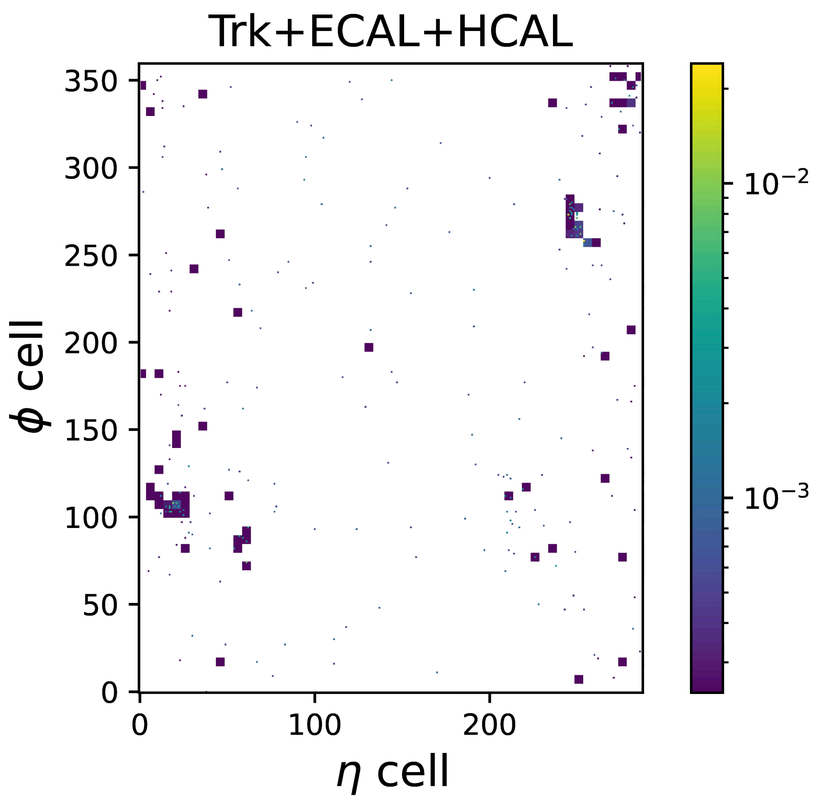


ConvAE reconstruction: a QCD test event

INPUT

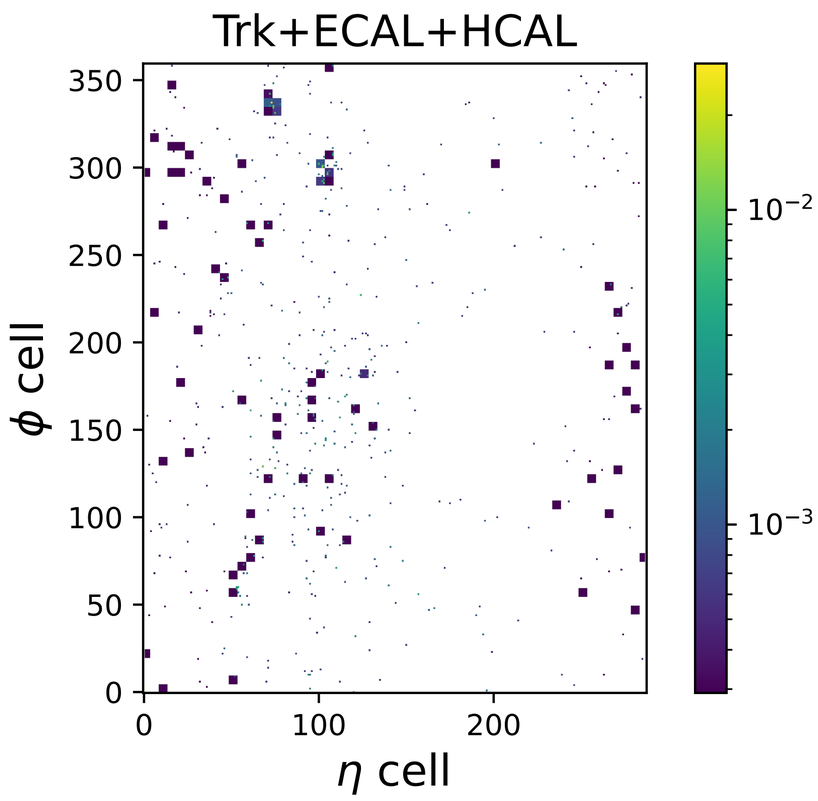


RECONSTRUCTION

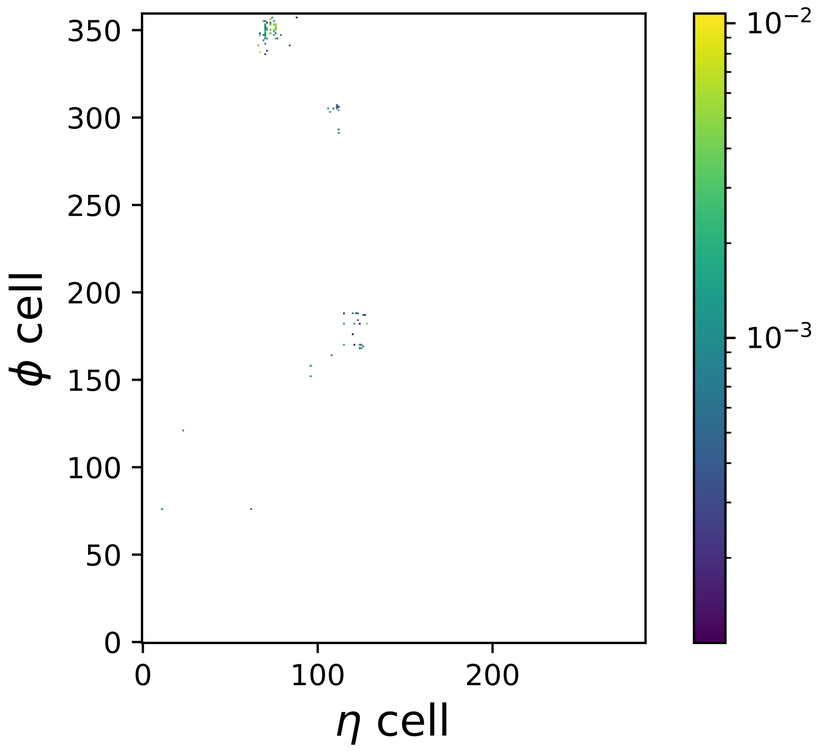


ConvAE reconstruction: a SUEP(1 TeV) test event

INPUT



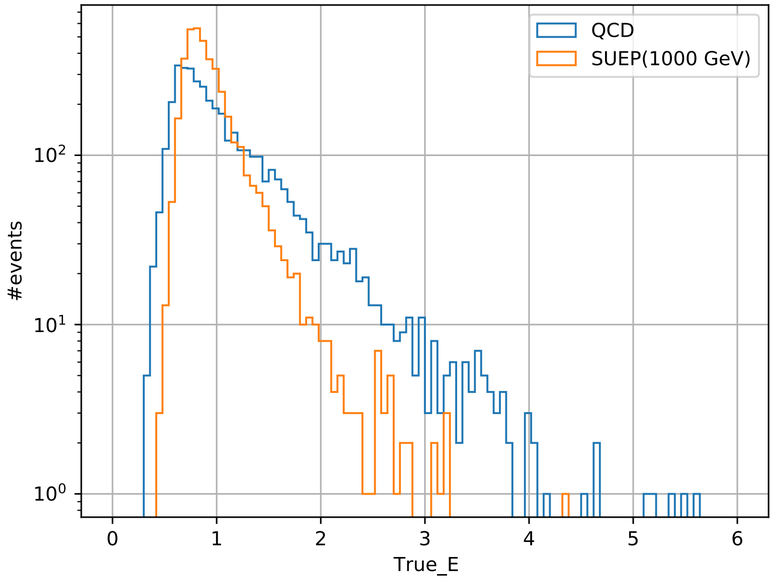
RECONSTRUCTION

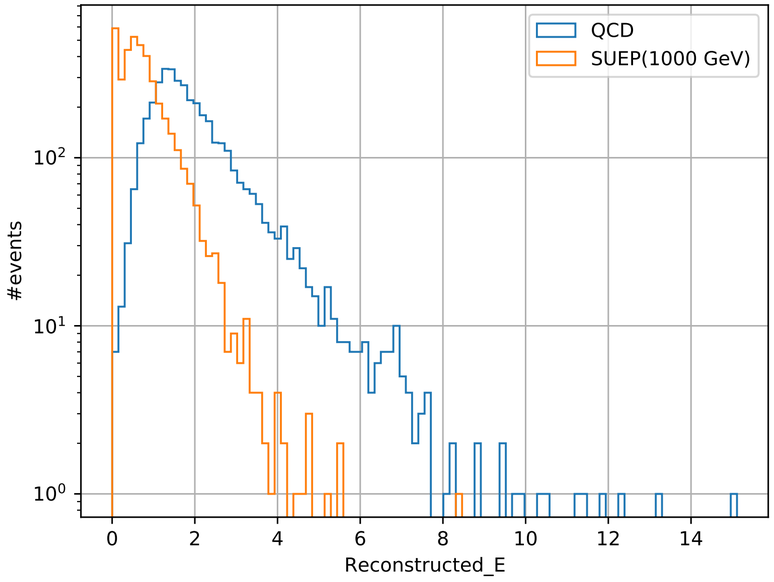


True E_T vs Reconstructed E_T

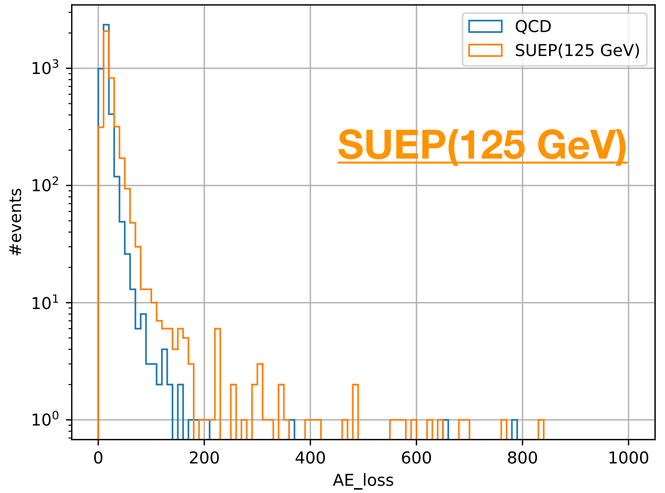
- Sum of all pixels' E_T

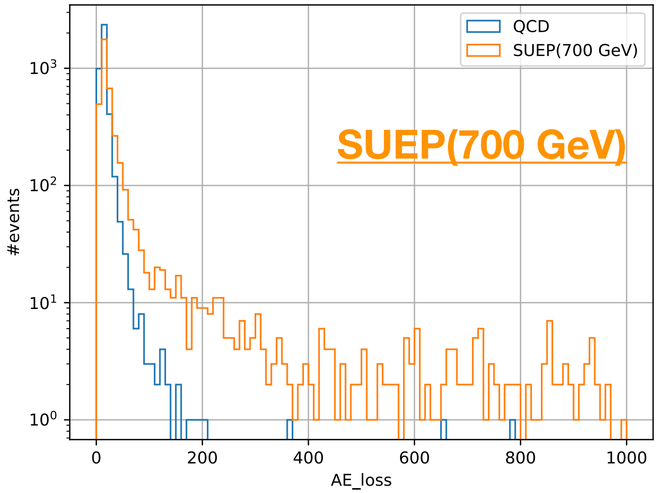
X_{test} : 4k QCD events
X_{test} : 4k SUEP events

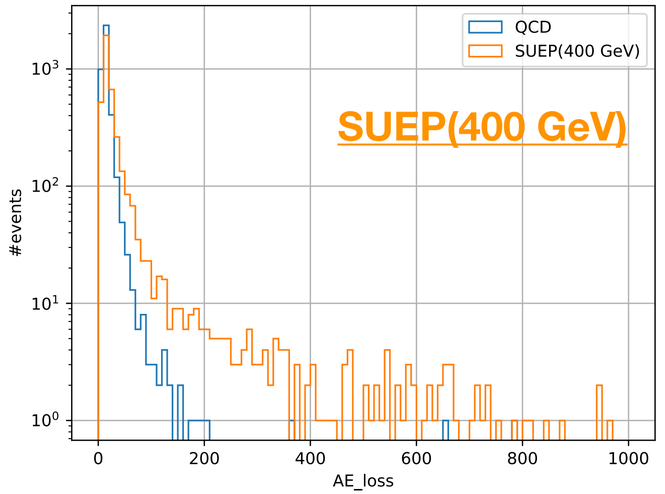


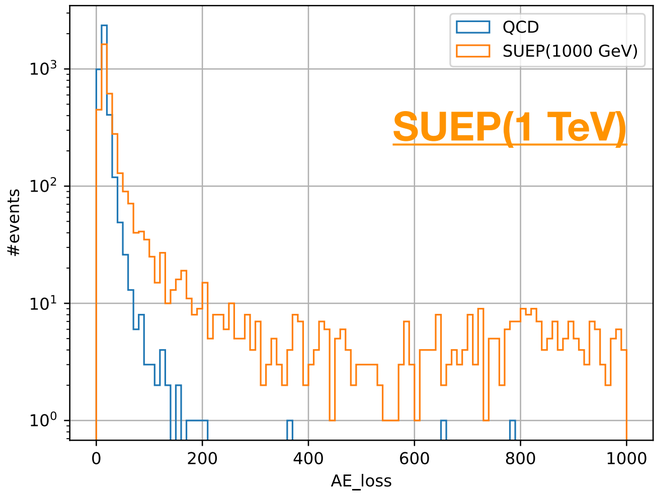


ConvAE loss for anomaly detection

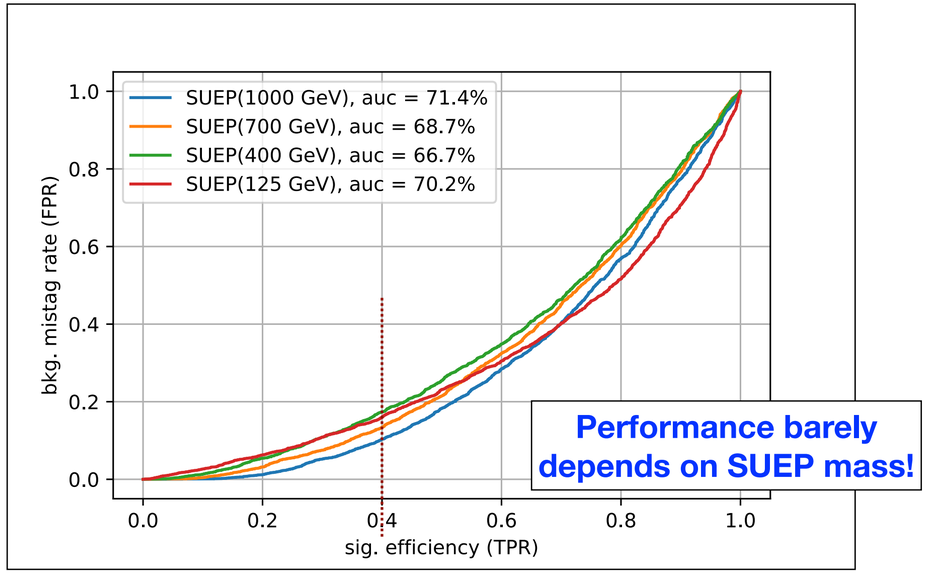








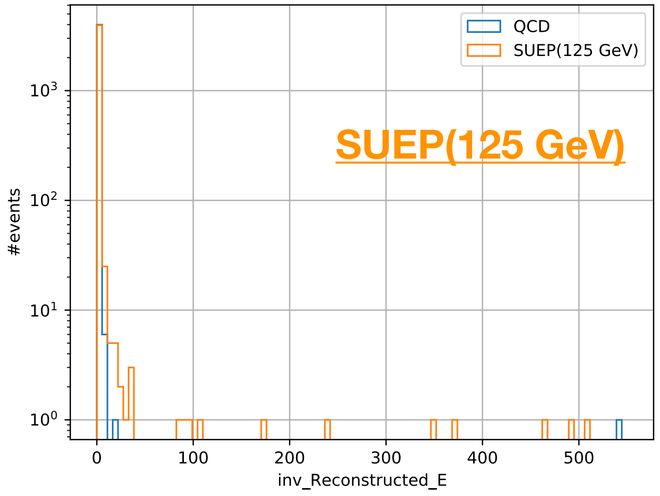
X_{test} : 4k QCD events
X_{test} : 4k SUEP events

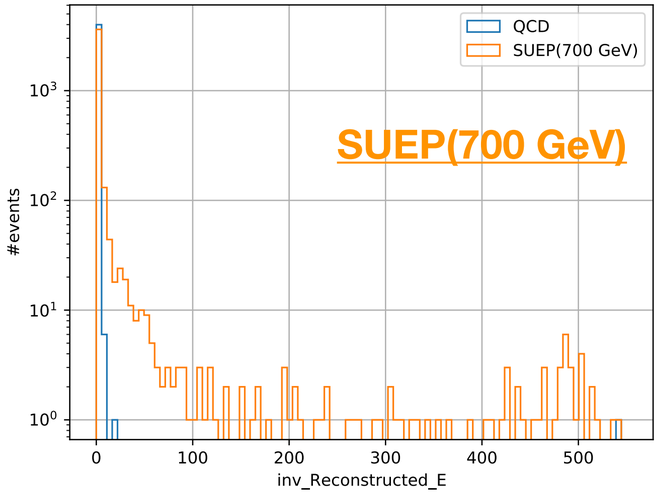


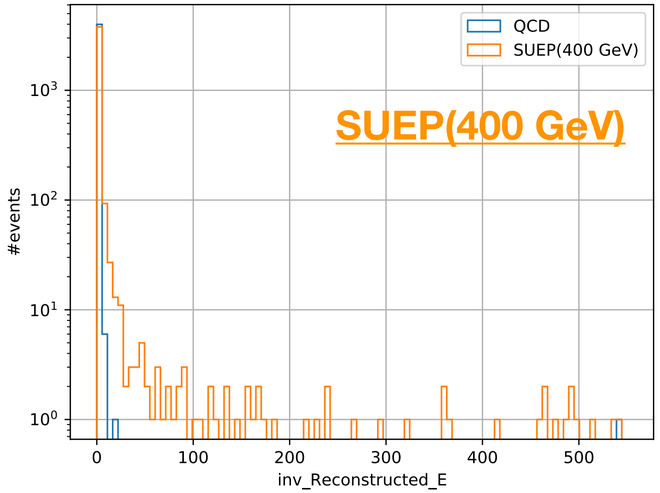
Performance barely depends on SUEP mass!

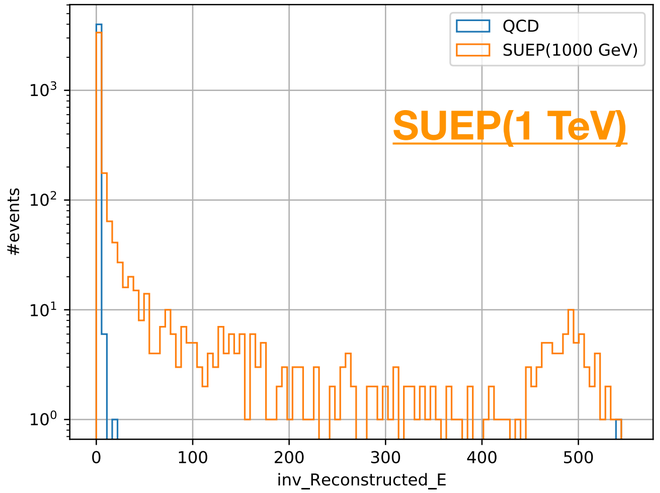
	Signal eff.	Bkg. mistag rate
SUEP(1 TeV)	40%	10.3%
SUEP(700 GeV)	40%	13.4%
SUEP(400 GeV)	40%	17.4%
SUEP(125 GeV)	40%	16.0%

1/reconstructed E_T for anomaly detection

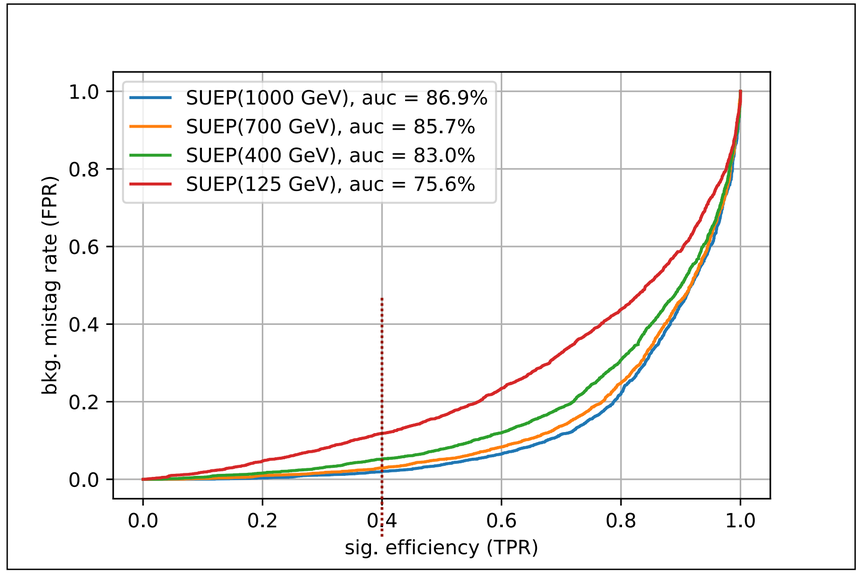








X_{test} : 4k QCD events
X_{test} : 4k SUEP events



	Signal eff.	Bkg. mistag rate
SUEP(1 TeV)	40%	2.0%
SUEP(700 GeV)	40%	2.9%
SUEP(400 GeV)	40%	5.2%
SUEP(125 GeV)	40%	11.9%

Conclusions

- A **convolutional neural networks-based autoencoder** (or ConvAE) has been developed for **real-time anomaly (non-QCD-like events) detection in a high-level trigger system at the LHC**
  - Data are represented as RGB images, i.e., energy deposits in CMS inner-tracker, ECAL and HCAL
  - The biggest challenge, **highly-sparse data**, has been tackled by using **1/Dice coefficient** as a loss function
- **ConvAE inference time:**

CPU: Intel(R) Core(TM) i5-9600KF CPU 3.70GHz	~20 ms

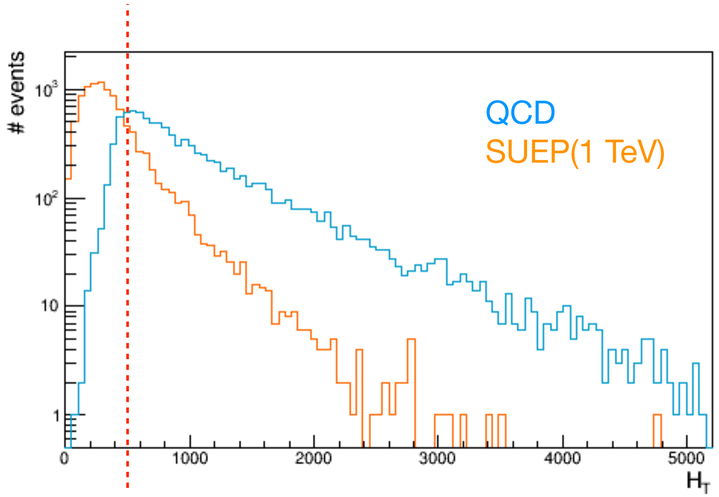
- For **Soft Unclustered Energy Patterns (SUEP)** detection:

		Bkg. mistag rate	
	Signal eff.	ConvAE loss	1/reconstructed E
SUEP(1 TeV)	40%	10.3%	2.0%
SUEP(700 GeV)	40%	13.4%	2.9%
SUEP(400 GeV)	40%	17.4%	5.2%
SUEP(125 GeV)	40%	16.0%	11.9%

- Performance comparison with supervised learning techniques is ongoing
- We plan on testing the performance for additional new physics signals
- *Documentation is underway!*

Backup slides

Events selection



- **Event selection:**
  - $|\eta| < 2.5$
  - Total transverse energy (H_T) > 500 GeV (typical at the HLT after Level-1 trigger selection in Run3, e.g., in CMS)
    - QCD selection efficiency: **~85%**
    - SUEP selection efficiency: **~2.1%** (125 GeV), **~10.4%** (400 GeV), **~18.4%** (700 GeV), **~22.7%** (1 TeV)

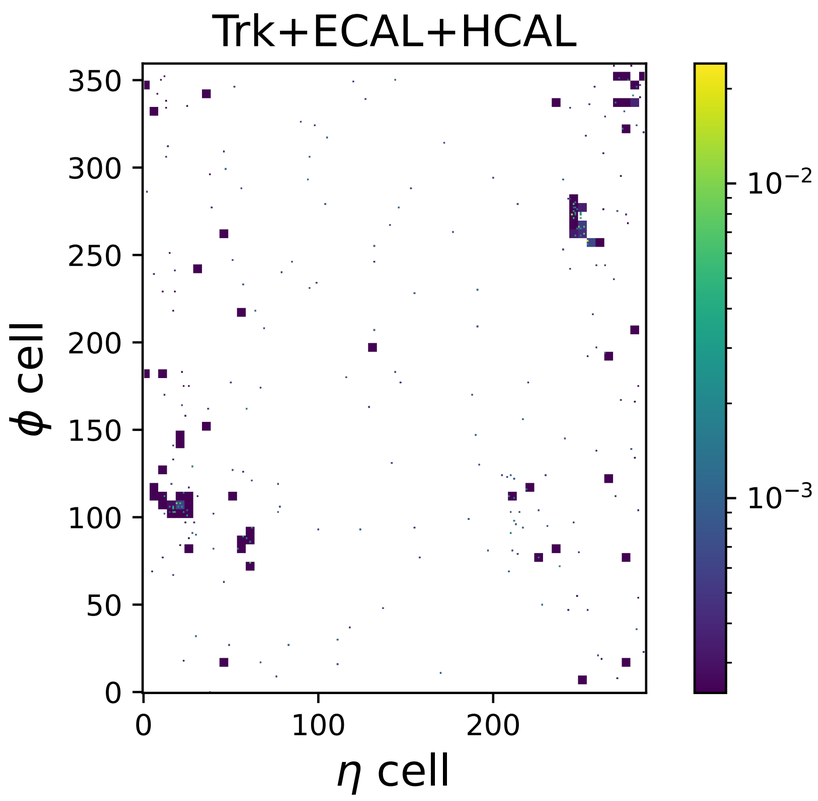
ConvAE summary

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 288, 360, 3)]	0
conv2d (Conv2D)	(None, 96, 120, 128)	3584
batch_normalization (BatchNo	(None, 96, 120, 128)	512
p_re_lu (PReLU)	(None, 96, 120, 128)	1474560
conv2d_1 (Conv2D)	(None, 48, 60, 64)	73792
batch_normalization_1 (Batch	(None, 48, 60, 64)	256
p_re_lu_1 (PReLU)	(None, 48, 60, 64)	184320
conv2d_2 (Conv2D)	(None, 24, 30, 32)	18464
batch_normalization_2 (Batch	(None, 24, 30, 32)	128
p_re_lu_2 (PReLU)	(None, 24, 30, 32)	23040
conv2d_3 (Conv2D)	(None, 12, 15, 16)	4624
batch_normalization_3 (Batch	(None, 12, 15, 16)	64
p_re_lu_3 (PReLU)	(None, 12, 15, 16)	2880
conv2d_4 (Conv2D)	(None, 6, 5, 8)	1160
batch_normalization_4 (Batch	(None, 6, 5, 8)	32
p_re_lu_4 (PReLU)	(None, 6, 5, 8)	240
p_re_lu_4 (PReLU)	(None, 6, 5, 8)	240
conv2d_transpose (Conv2DTran	(None, 12, 15, 16)	1168
batch_normalization_5 (Batch	(None, 12, 15, 16)	64
p_re_lu_5 (PReLU)	(None, 12, 15, 16)	2880
conv2d_transpose_1 (Conv2DTr	(None, 24, 30, 32)	4640
batch_normalization_6 (Batch	(None, 24, 30, 32)	128
p_re_lu_6 (PReLU)	(None, 24, 30, 32)	23040
conv2d_transpose_2 (Conv2DTr	(None, 48, 60, 64)	18496
batch_normalization_7 (Batch	(None, 48, 60, 64)	256
p_re_lu_7 (PReLU)	(None, 48, 60, 64)	184320
conv2d_transpose_3 (Conv2DTr	(None, 96, 120, 128)	73856
batch_normalization_8 (Batch	(None, 96, 120, 128)	512
p_re_lu_8 (PReLU)	(None, 96, 120, 128)	1474560
conv2d_transpose_4 (Conv2DTr	(None, 288, 360, 3)	3459
batch_normalization_9 (Batch	(None, 288, 360, 3)	12
activation (Activation)	(None, 288, 360, 3)	0

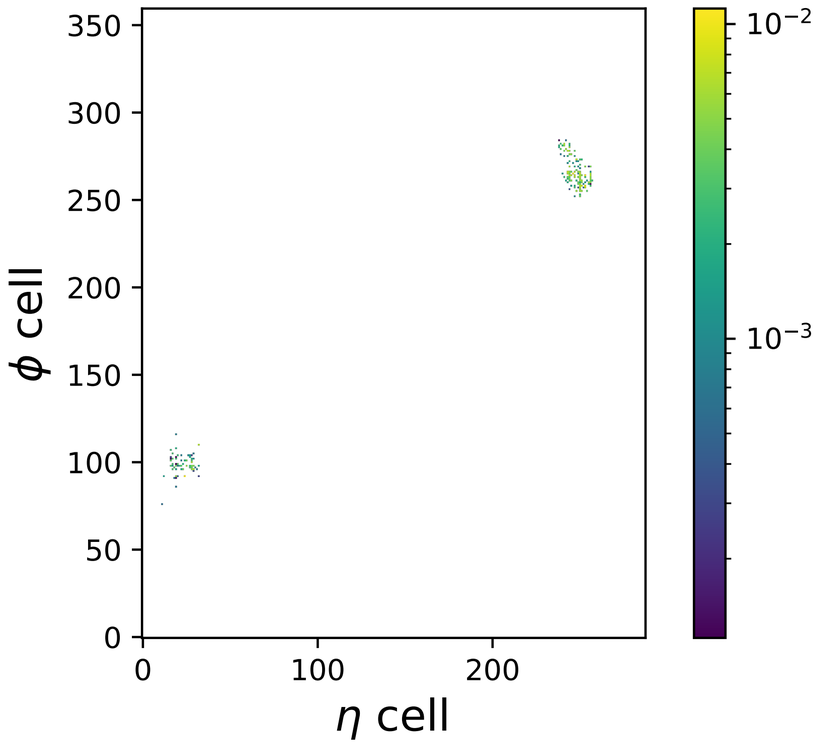
Total params: 3,575,047
Trainable params: 3,574,065
Non-trainable params: 982

ConvAE reconstruction: a QCD test event

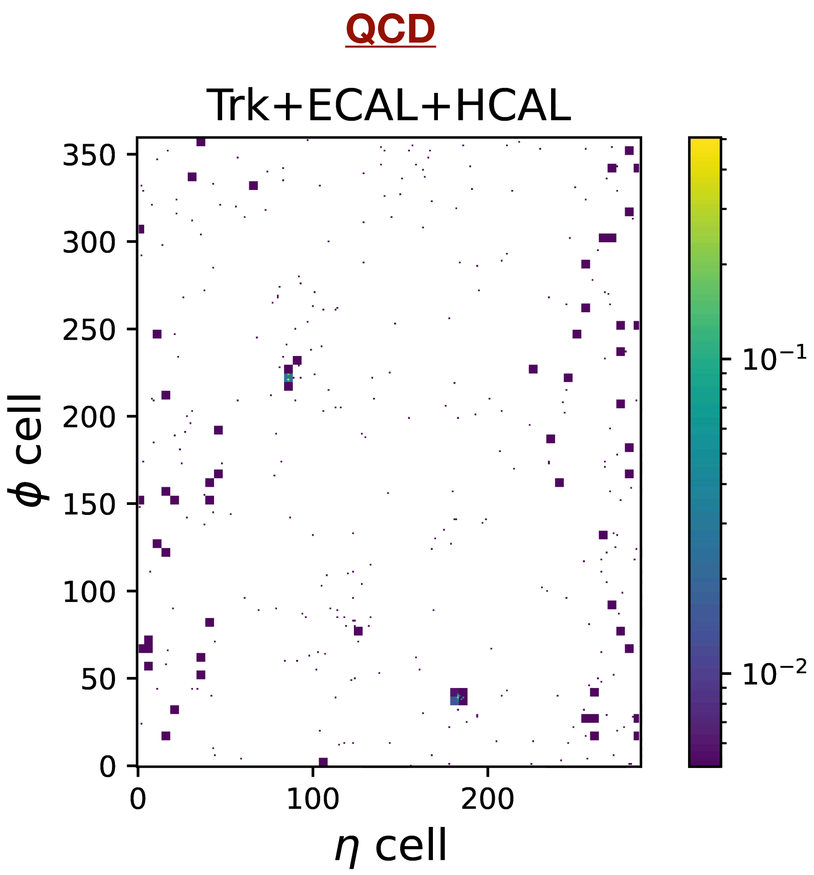
INPUT

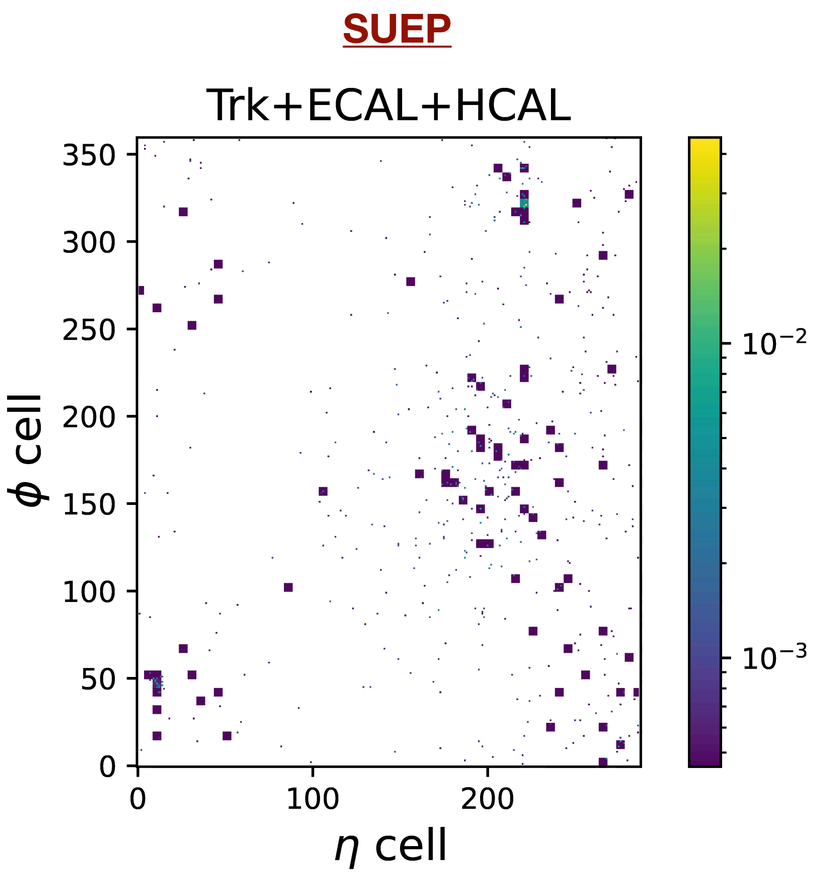


RECONSTRUCTION



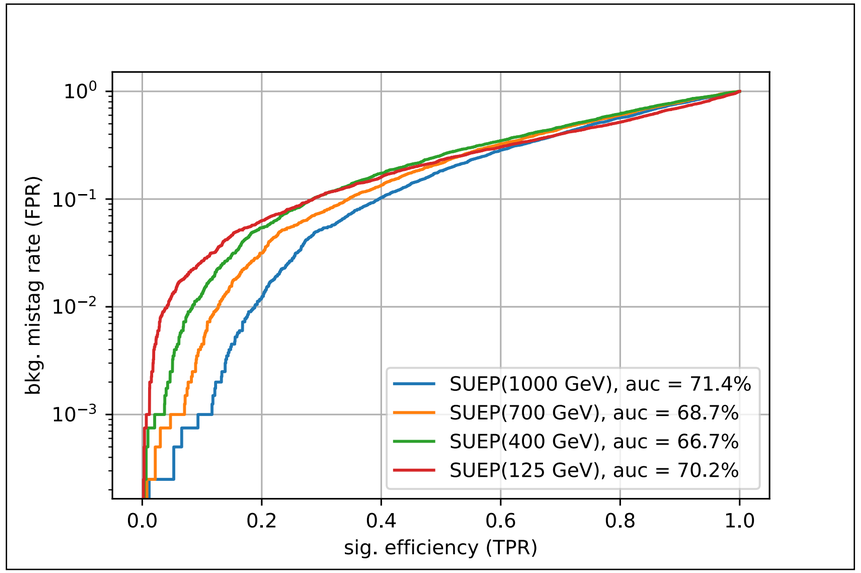
ConvAE reconstruction: several QCD and SUEP(1 TeV) test events



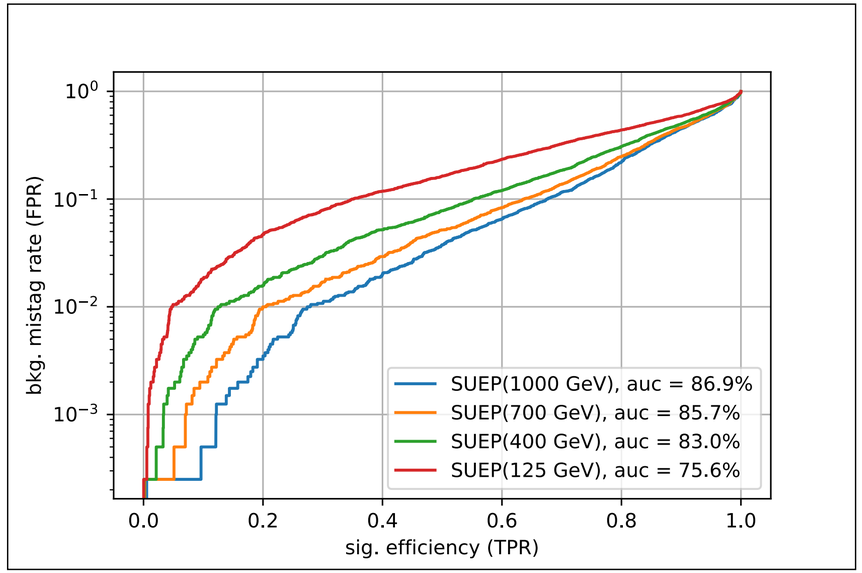


ROC curves in log scale

ConvAE loss for anomaly detection

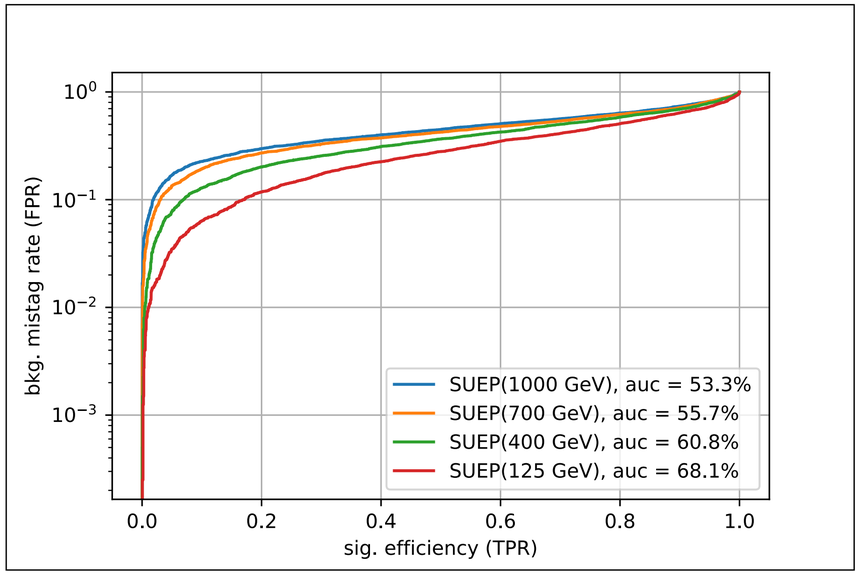


1/reconstructed E_T for anomaly detection



Additional ROC curves in log scale

1/True E_T



reconstructed E_T